Artificial Neural Network-Based-Receiver for Eigenvalue-Modulated Signal in Presence of Optical CFO

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Abstract We demonstrate the demodulation of an eigenvalue-modulated signal combining an artificial neural network with a CFO compensation. The proposed demodulator achieves successful demodulation with power penalty < 1 dB in the presence of CFO within 1 GHz at 2.5 Gb/s in experiments.

Introduction

Optical eigenvalue modulation^[1] that is based on the inverse scattering transform (IST)^[2] is a promising approach for overcoming the nonlinear Kerr limit in optical fiber communication systems^{[3]–[12]}. In recent years, the IST has become well-known as a nonlinear Fourier Transform (NFT). The eigenvalues of the eigenvalue equation associated with the nonlinear Schrödinger equation (NLSE) are invariant even though the signal waveform and frequency spectrum change during propagation in optical fiber.

To increase the transmission capacity, various eigenvalue modulation schemes have been proposed, such as the on-off encoding of multieigenvalues^{[4],[5]} and phase shift keying modulation of the spectral amplitude for multi-soliton pulses^[6]. Furthermore, to facilitate improvement in the received power margin, several recent studies have investigated machine learning-based demodulation methods for eigenvalue modulation, such as classification^{[7]–[9]} and equalization^{[10],[11]}. Demodulation methods based on time-domain (TD) artificial neural networks (ANNs) outperformed the conventional IST-based demodulation method in terms of the bit error rate (BER) performance with a large power margin^{[7],[8]}. Moreover, we proposed an eigenvalue domain (ED)-ANNbased demodulation method, which does not reguire model training for each transmission distance^[9]. However, a detailed analysis of the effects of the carrier frequency offset (CFO) on ANN receiver for eigenvalue-modulated signal is yet to be reported.

In this paper, we numerically and experimentally investigate the generalization performances of ED-ANN-based demodulator on CFO. Moreover, we propose to combine an ED-ANNbased demodulator with a CFO compensation method based on IST. The proposed demodulator achieves successful demodulation with power penalty < 1 dB in the presence of CFO within 1 GHz at 2.5 Gb/s in experiments.

Eigenvalue modulation and demodulation

In this work, we employed eigenvalue modulation with on-off encoding^[5] of four eigenvalues (N = 4) and an ED-ANN based-demodulator. Fig. 1 shows the modulation and demodulation schemes. This modulation begins with a sequence (seq.) of N bits encoded into an eigenvalue pattern, which is the on-off state of the complex eigenvalue ζ_n . Next, the encoded eigenvalue pattern is converted into an input pulse by using IST^[2]. Then, the converted pulse corresponds to a symbol carrying N information bits. The optical eigenvalue-modulated signal is transmitted over the optical fiber transmission line. At the receiver, the received pulse is converted into an eigenvalue pattern using IST. The real and imaginary parts of the detected eigenvalues are input to the ANN, which outputs the probability parameter of the bit seq. that corresponds to the detected eigenvalue pattern. For a sampling rate of 32 samples per pulse, the number of detected eigenvalues including the continuous spectrum, is also 32, and there are 64 input elements comprising 32 real and 32 imaginary parts of those eigenvalues. The num-



Fig. 1: Eigenvalue modulation and demodulation^[9]



Fig. 2: Overview of the proposed CFO compensation

ber of output elements is 16, corresponding to the number of eigenvalue patterns (i.e. $2^4 = 16$).

CFO compensation

To emphasize the generalization performance of the CFO, we propose the combining a CFO estimation method in ED with the ED-ANN demodulator. In related work^[12], CFO is estimated in the ED and compensated in the scattering parameter $b(\zeta)$ domain for *b*-modulation. It is expected that the CFO estimation in the ED is more accurate than that in linear frequency domain particularly for CFO below a half of baudrate. In this work, we estimate CFO in the ED and compensate it in the TD for an on-off encoded signal to suppress eigenvalue position slips at high soliton frequency.

Fig. 2 shows an overview of the proposed CFO compensation method. In the eigenvalue domain, the real part of the eigenvalue $\operatorname{Re}[\zeta]$ refers to the soliton frequency^[3]. Regarding the frequency offset, the following relationship between the TD signal u(T) and eigenvalue ζ is well-known,

$$u(T)\exp(-i2\pi FT) \iff \zeta - \pi F,$$
 (1)

where u(T), T and F represent the normalized complex amplitude, time, and frequency, respectively. Hence, the frequency offset f_{offset} in the actual TD is converted to a shift $\Delta \zeta_{real}$ of the real part of the eigenvalue in the ED. In the proposed method, the estimated frequency \hat{f}_{offset} is obtained from the eigenvalues ζ_{train} and ζ_{pilot} of the training pulse and pilot pulses,

$$\hat{f}_{offset} = \frac{\overline{\Delta \zeta_{real}}}{\pi t_0} = \frac{\overline{\operatorname{Re}[\zeta_{train}]} - \overline{\operatorname{Re}[\zeta_{pilot}]}}{\pi t_0}, \quad (2)$$

where t_0 is the base time satisfying $T = t/t_0$ and t is the actual time. The CFO of the test data is compensated for in TD by using the estimated frequency offset \hat{f}_{offset} . For a practical system, the ED-ANN can cover CFO fluctuations by inserting periodic pilot soliton pulses.



Simulations

Fig. 3 shows the simulation model. For eigenvalue modulation, we used the four optical eigenvalues $\zeta = \{-0.25 + i0.25, 0.25 + i0.25, -0.25 + i0.5, 0.25 + i0.5\} \in \mathbb{C}$. The modulation was performed at 10 Gsample/s, the pulse duration was 1.6 ns, and the bit rate was 2.5 Gb/s. We confirmed the B-to-B operation to demonstrate its utility. We assumed that the phase noise was negligible, and that the CFO was constant in each BER test.

ANN configuration and parameters for demodulation (demod.) are described in the previous section. We used a three-layer perceptron configuration and a rectified linear unit activation function. The number of hidden units was set to 256. We used the soft max function as the output function, and the cross-entropy error function as the loss function. We prepared a block signal that consists of 32 pulses of the pilot signal, 2,468 pulses of the dummy signal, random pulse sequences of 10,000 for the training and 50,000 pulses for the validation and BER tests. The block signal length was 100 μ s. The ANN was trained using the Adam optimizer^[13], and the training data was uniformly extracted from available data sets with OSNR values in the 0-20 dB range. To avoid over-fitting, the training was terminated when the validation result (obtained once every 50 epochs) ceased to improve^[14]. For CFO compensation (comp.), we used 32 pilot pulses having the eigenvalue pattern "0010" ($\zeta = 0.25 + i0.25$).

Fig. 4 shows the BER curves obtained using test data of various CFOs and the ED-ANN demodulator trained with training data of CFO=0 Hz. The ED-ANN without CFO compensation is valid for a CFO below 125 MHz with a small power penalty < 1 dB under the modulation conditions of this simulation. For CFO values over 1 GHz without CFO compensation, the ED-ANN trained with data of CFO=0 Hz cannot demodulate the received signal because of the large eigenvalue shift as shown in Fig. 5(a). Using



the proposed CFO compensation, we can see that the eigenvalue shifts $\Delta \zeta_{real}$ are compensated from Fig. 5(b). As a result, the ED-ANN demodulator with CFO compensation achieved a successful demodulation with almost no OSNR penalty in the presence of CFO within 2.5 GHz.

Experiments

Fig. 6 shows an experimental set up for demonstration of the proposed CFO compensation and ED-ANN demodulation. For eigenvalue modulation, the same eigenvalue pattern comprising four optical eigenvalues and modulation conditions described in the previous section for the simulation were considered. An eigenvalue-modulated signal was generated by an offline digital signal processing (DSP). The optical signal was generated using an arbitrary waveform generator (AWG) and an IQ modulator. The amplified spontaneous emission (ASE) noise source before the receiver was used to measure the BER curves. At the receiver, the required DSP for demodulation was performed offline at 20 Gsample/s. ANN configuration, training condition, and CFO compensation parameters were maintained identical to those described in the simulation. We changed the CFO by adjusting wavelength of the local oscillator (LO) light. When the set point of wavelength λ_{LO} of the LO was 1550.012 nm, the CFO was minimized. Hence, the ED-ANN was trained for λ_{LO} =1550.012 nm and the test data were collected in the range of λ_{LO} =1550.012–1550.032 nm.

Fig. 7 shows the BER curves with varying wavelengths of LO. $\Delta\lambda$ denotes the difference in wavelength between the training and test data. Without the CFO compensation, a large OSNR





penalty due to the eigenvalue shift was observed for $\Delta\lambda$ over 2 pm (~250 MHz). On the other hand, the ED-ANN with CFO compensation can demodulate an eigenvalue-modulated signal even for $\Delta\lambda = 20$ pm (~2.5 GHz). The OSNR requiered to achieve the forward error correction (FEC) limit of 3.8×10^{-3} is shown in Fig. 8. By using the proposed CFO compensation method, the OSNR penalty at the FEC limit can be suppressed below 1 dB when $\Delta\lambda < 8$ pm (~1 GHz).

Conclusions

We proposed the demodulation of an eigenvaluemodulated signal by combining an ED-ANN with an IST-based CFO compensation method. By performing both numerical simulations and proofof-concept experiments, we successfully demonstrated a demodulation with OSNR penalty < 1dB in the presence of CFO within 1 GHz at 2.5 Gb/s.

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References

- A. Hasegawa and T. Nyu, "Eigenvalue communication", *IEEE/OSA J. Lightw. Technol.*, vol. 11, no. 3, pp. 395– 399, Mar. 1993.
- [2] M. J. Ablowitz and H. Segur, *Solitons and the Inverse Scattering Transform*. Philadelphia, PA, USA: SIAM, 1981.
- [3] S. K. Turitsyn, J. E. Prilepsky, S. T. Le, S. Wahls, L. L. Frumin, M. Kamalian, and S. A. Derevyanko, "Nonlinear fourier transform for optical data processing and transmission: Advances and perspectives", OSA Optica, vol. 4, no. 3, pp. 307–322, Mar. 2017.
- [4] S. Hari, M. I. Yousefi, and F. R. Kschischang, "Multieigenvalue communication", *IEEE/OSA J. Lightw. Technol.*, vol. 34, no. 13, pp. 3110–3117, Jul. 2016.
- [5] T. Kodama, T. Zuiki, K. Mishina, and A. Maruta, "Hyper multilevel modulation based on optical eigenvalue multiplexing", in *Proc. Photon. in Switching and Computing* (*PSC*), Limassol, Cyprus, Sep. 2018, pp. 1–2.
- [6] V. Aref and H. Buelow, "Design of 2-soliton spectral phase modulated pulses over lumped amplified link", in *Proc. 42nd European Conf. on Opt. Commun. (ECOC)*, Düsseldorf, Germany, Sep. 2016, pp. 409–411.
- [7] R. T. Jones, S. Gaiarin, M. P. Yankov, and D. Ziber, "Time-domain neural network receiver for nonlinear frequency division multiplexed systems", *IEEE Photon. Technol. Lett.*, vol. 30, no. 12, pp. 1079–1082, Jun. 2018.
- [8] K. Mishina, S. Yamamoto, T. Kodama, Y. Yoshida, D. Hisano, and A. Maruta, "Experimental demonstration of neural network based demodulation for on-off encoded eigenvalue modulation", in *Proc. 45th European conf. on Opt. Commun. (ECOC)*, Dublin, Ireland, Sep. 2019, pp. 1–4.
- [9] K. Mishina, S. Sato, S. Yamamoto, Y. Yoshida, D. Hisano, and A. Maruta, "Demodulation of eigenvalue modulated signal based on eigenvalue-domain neural network", in *Proc. The Optical Fibrer Commun. Conf.* (*OFC*), San Diego, CA, USA, Mar. 2020, pp. 1–3.
- [10] Y. Wu, L. Xi, X. Zhang, Z. Zheng, J. Wei, S. Du, W. Zhang, and X. Zhang, "Robust neural network receiver for multiple-eigenvalue modulated nonlinear frequency division multiplexing system", OSA Opt. Exp., vol. 28, no. 12, pp. 18304–18316, Jun. 2020.
- [11] O. Kotiyar, M. Pankratova, M. Kamalian-Kopae, A. Vasylchenkova, J. E. Prilepsky, and S. K. Turitsyn, "Combining nonlinear fourier transform and neural networkbased processing in optical communications", OSA Opt. Lett., vol. 45, no. 13, pp. 3462–3465, Jul. 2020.
- [12] Z. Zheng, X. Zhang, R. Yu, L. Xi, and X. Zhang, "Frequency offset estimation for nonlinear frequency division multiplexing with discrete spectrum modulation", *OSA Opt. Exp.*, vol. 27, no. 20, pp. 28 223–28 238, Sep. 2019.
- [13] D. Kingma and J. Ba, "Adam: A method for stochastic optimization", in *Proc. 3rd International Conf. for Learning Representation (ICLR)*, San Diego, CA, USA, May 2015, pp. 1–15.
- [14] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learn-ing*. Cambridge, MA, USA: MIT Press, 2016.